Creation of Knowledge & Meaning
Manifested via Cortical Singularities in Cognition
Towards a Methodology to Understand Intentionality and Critical Behavior in Neural Correlates of Awareness

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Abstract—Experimental and theoretical approaches aiming at the establishment of neural correlates of higher cognitive functions and awareness have been extensively studied in the past decade. Information-theoretical indices are useful tools in establishing quantitative metrics when analyzing data of cognitive experiments. In this work we report a systematic statistical analysis of multiple runs of ECoG measurements over the rabbit visual cortex. The results are interpreted invoking the concept of Pragmatic Information, which is complementary to the Shannon Entropy Index. We interpret these findings based on a dynamical system approach to brains and cognition. We identify large-scale synchronization across broad frequency band as potential manifestation of the 'aha' effect, indicating the construction of knowledge and meaning from input sensory data and leading to awareness experience.

Keywords - Electrocorticogram, Hilbert Transform, Synchronization; Analytic Amplitude; Analytic Phase; Criticality; Awareness; Cognition.

I. INTRODUCTION

Neurophysiological processes manifesting higher cognition and consciousness have been intensively studied by fMRI, PET, MEG, and other advanced techniques, and numerous spectacular successes have been reported in the past decade [1-5]. While these brain imaging techniques provide useful information on brain structure and function, still measuring evoked potentials over the cortex through electrocorticograms (ECoG) and over the scalp by electroencephalograms (EEG) have distinct benefits by providing direct and prompt information on the electrochemical processes underlying brain operation; for a comprehensive review see the new monograph by Freeman and Quiroga [6]. Extensive studies have been conducted on developing information-theoretical indices to characterize EEG behavior [7, 8], with special efforts to detect the onset of synchronization of neural activity across large cortical areas related to higher cognition [9, 10].

In dynamical brain models, brains can be viewed as thermodynamic systems operating near the state of criticality, with the ability to intermittently exhibit synchronization-de-synchronization transitions [11-13]. Pragmatic information has been introduced from semiotics as a complementary concept to information, to characterize meaning and knowledge [14, 15]. Meaning, knowledge and intentions can be derived from actions, and pragmatic information indices intend to capture the goal-oriented aspect of the cognitive cycle. Pragmatic information indices are related to physical quantities such as energy, work, force, and distance.

The present work is the continuation of studies with rabbit electrocorticogram (ECoG) data [16, 17]. Previous studies showed that synchronization effects observed in ECoG arrays have significant invariance over a broad-range of frequencies, including gamma-, beta-, alpha-, and theta-bands. In the present study we extend the analysis to a series of experiments (39 runs) over the visual cortex of the rabbit. Our goal is to conduct a robust analysis based on multiple runs to obtain statistically significant discrimination among various stages of the cognitive process.

We start with brief characterization of the rabbit ECoG experiments, followed by introducing the Hilbert transform-based signal processing approach. We define and test a variety of indices related to pragmatic information, which take into consideration the amount of work that is required to create knowledge expressed in meaningful actions. Several of the indices can be interpreted as equivalent forces driving meaningful action based on the knowledge previously created. Next we describe the obtained results, which point to a clear synchronization effect across frequencies during intensive cognitive activity, indicating the detection and classification of previously learnt conditioned stimuli. Finally, we point to some limitations of our analysis and how to overcome such limitations in future research. Our work has the potential to shed light on constructive aspects of intention, creativity, in the context of universal values and behavioral responses, for the future benefit and the peaceful development of humanity [18, 19].
II. DESCRIPTION OF ECoG EXPERIMENTS AND DATA PREPROCESSING

Experimental data obtained from intracranial arrays of 8x8 electrodes implanted over the visual cortex of rabbits at the Freeman Neurophysiology Lab at UC Berkeley [20-23]. Discrimination has been learnt by the animals under the classical conditioning paradigm, when one stimulus was reinforced (CS+) and the other was not (CS−). Once the animals have been trained, experiments have been conducted with CS+ and CS− stimuli. A single experiment contained 6 s, in which the first half (3 s) has been used to establish the background reference state. At time 3 s, a stimulus (light flash) has been presented to the animal and the response has been recorded for 3 s. The first and last 0.5 s are omitted as those periods are used for the proper widowing functions.

We follow the preprocessing steps as described in previous studies [16]. Accordingly, first we analyze the 64-channel ECoG signals, perform preprocessing and band-pass filtering over each channel. Next we determine the analytic signals after Hilbert transforming the band-passed ECoG data. The analytic amplitude of each channel is denoted as $A_j(t)$, $i = 1,..., 64$. We use notation $P_i(t)$ for the analytic phase, $P_i(t)$, $i = 1,..., 64$.

Band-pass filters are applied in the theta, alpha, beta and gamma bands with the following parameters given in Table I. The applied Hilbert transform methodology and the analytic signal construction followed the approach described in [15, 18].

Table I. Parameters of the pass band filters over various frequency bands

<table>
<thead>
<tr>
<th>Frequency Band</th>
<th>$f_{\text{stop}}$ Hz</th>
<th>$f_{\text{passL}}$ Hz</th>
<th>$f_{\text{passH}}$ Hz</th>
<th>$f_{\text{stopH}}$ Hz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theta</td>
<td>3</td>
<td>4</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Alpha</td>
<td>8</td>
<td>9</td>
<td>11</td>
<td>12</td>
</tr>
<tr>
<td>Beta</td>
<td>12.5</td>
<td>16.5</td>
<td>21</td>
<td>24</td>
</tr>
<tr>
<td>Gamma</td>
<td>24</td>
<td>30</td>
<td>36</td>
<td>40</td>
</tr>
</tbody>
</table>

The comprehensive analysis of all 64 channels in the 39 experiments, over various frequency bands produces a lot of data, which cannot be reproduced fully in this report. Instead, we illustrate the behavior of the ECoG signals and the analytic signals over the theta and gamma bands for two experiments, i.e., #1 and #39. Figure 5 shows filtered ECoG signals in all 64 channels for 2 trials (first and last) for the theta and gamma bands. The figures are divided into four sets of graphs each of them with four subgraphs which are: signal amplitudes (SA) of the 64 channels (top), the 64 channel’s analytic amplitude (AA) (middle top), the analytic phase of the signals after Hilbert transform (middle bottom), and the absolute analytic frequency derived from the instantaneous phase differences (bottom).

Figure 1 shows that the 64 channels have high synchrony over most of the time instances, with the exception of the post-stimulus period 3−4 s. There is significant variation over the post-stimulus period in the ECoG signals (SA), but the most prominent changes are seen in the analytic amplitudes (AA). The analytic phase value (AF) exhibit intermittent variations as time evolves, which is exemplified by the instantaneous frequencies (IF) in the form of large diverse spikes. The above conclusions are true both for the theta and gamma bands, however, the gamma band exhibits much more intensive variations of the instantaneous frequencies. Moreover, in the gamma band there seem to be a few (3 or 4) regions in the post-stimulus period with large SA and AA values, separated by intermittent drop in SA and AA.

It is difficult to make more quantitative conclusions based on these characteristics of AA, SA, AP, and IF. To better discriminate the effects, in the next section we introduce several information theoretic indices. Note that the spatially distributed AA and SA patterns carry useful information concerning the meaning of the signal to the subject, as it has been demonstrated in various experiments [1, 10, 15, 21, 22]. Therefore, eventually, we aim at deriving classification methods based on the distributed SA and AA patterns. However, this question is outside the scope of this paper.

In the next section we introduce various statistical measures over different bands in order to analyze the fine structure of the post-stimulus response period. We show detailed results obtained for various bands. This helps to illustrate major features of the Hilbert analysis and its usefulness in deriving the pragmatic information indexes.

III. INFORMATION THEORETIC INDICES BASED ON PRAGMATIC INFORMATION

In this section we develop a qualitative characterization of the de-synchronization effect described previously. We describe the pragmatic information index [14, 15]; then we introduce several modified versions of the original indices [23]. We denote the 64 scalar values of the squared analytic amplitude as $A^2_j(t)$, which form a vector at each time step $A^2(t)$. The 64-dimensional vector $A^2(t)$ serves as an order parameter. The rate of pattern evolution is proportional to the Euclidean distance, $D(t)$, between successive time points:

$$D_t = \text{dist}(A^2(t), A^2(t-1)) = |A^2(t) - A^2(t-1)|.$$  \hspace{1cm} (1)

The ratio of mean rate of free energy dissipation across the array $<A^2(t)>$, to the rate of change in the order parameter, $D(t)$, defines a quantity, which can be called pragmatic information [14, 15]:

$$H(t) = \frac{<A^2(t)>}{D(t)}.$$  \hspace{1cm} (2)
Figure 1. Illustration of the analyzed rabbit ECoG data in experiments #1 and #39 filtered over different frequency bands. Each of the panels (a) to (d) have 4 subplots showing the 64 curves corresponding to the ECoG signals, analytic signals, unwrapped phases, and instantaneous frequencies, from top to bottom, respectively. (a) & (b): theta band signals filtered over pass band 4 Hz to 6 Hz; (c) & (d): gamma band signals filtered over pass band 30 Hz to 36 Hz respectively.
Here \(< >\) denotes the spatial ensemble average. In addition to the individual channels, we define the average over \(k=8\) groups of channels, defined as follows: \(\text{group} 1 = \{\text{for channels } j=1:8\} \), \(\text{group} 2 = \{j=9:16\} \), ..., \(\text{group} 8 = \{j=57:64\} \). These group averages will be useful to display the variation of the indices over the array, without giving details of individual channels. Following are the indexes relevant to our analysis [16, 23]:

- **Range (max-min) of Amplitude** \((\text{RA}_j)\) for each channel. The Range of Amplitude can be substituted by the squared analytic amplitude as originally introduced by Freeman [15]; we will also evaluate indexes using the signal amplitude, and the analytic amplitude.

- **Euclidean Distance**: can be calculated either for the whole lattice \((D_e)\) or for each of the \(k\) groups \((D_{ek})\). This quantity has been calculated originally using analytic amplitudes as in Eq.1; it can be calculated also using the analytic phase values.

- **Shannon Entropy Index** \((\text{SH}_j)\) for each channel. This quantity is computed with MATLAB entropy index function. This index has been evaluated in details in [23]. In the present study we do not use Shannon Information index, because it showed high dispersion and low reliability earlier, and thus seems not a suitable metric for our present purposes.

We are now ready to introduce the general form of Pragmatic Information Index \((H_\ast(t))\) as follows:

\[
H_\ast(t) = \frac{<\text{RA}_j(t)>}{D_e(t)}. 
\]  

(3)

We experiment with alternative definitions of the Pragmatic Information Index, by using 3 variants of the amplitude measure. Namely, \(\text{RA}_j\) in Eq. 3 can be substituted by either \(\text{RSA}\), \(\text{RAA}\), or \(\text{MA2}\), as defined below:

- **\(\text{RSA}(t)\)**: The Range of the Signal Amplitude;
- **\(\text{RAA}(t)\)**: The Range of the Analytical Amplitude;
- **\(\text{SAA}(t)\)**: The Squared Analytical Amplitude.

Each of these quantities can be defined as spatial ensemble average for the whole array, or for a specific group \(k\). They implement either temporal average over a specific interval \(T\) for \(\text{SAA}_T(t)\), \(\text{RSA}_T(t)\) and \(\text{RAA}_T(t)\), or can use instantaneous values in the case of \(\text{SAA}(t)\). Accordingly, the following Pragmatic Information Indices are introduced:

\[
\begin{align*}
\text{HRSA}_{k,T}(t) &= \frac{<\text{RSA}_{k,T}(t)>}{D_e(t)}, \\
\text{HRAA}_{k,T}(t) &= \frac{<\text{RAA}_{k,T}(t)>}{D_e(t)}, \\
\text{HSAA}_{k,T}(t) &= \frac{<\text{SAA}_{k,T}(t)>}{D_e(t)},
\end{align*}
\]

Note that \(\text{HSAA}_{k,T}(t)\) coincides with the original definition of \(H_\ast(t)\) in Eq. 3, if we take the instantaneous value without temporal averaging, and if the spatial average includes the whole array, not only a specific subgroup \(k\). \(\text{HRSA}_{k,T}(t)\) and \(\text{HRAA}_{k,T}(t)\) introduce alternative quantities, which involve granulation in space through groups \(k\) and also granulation in time through average or range evaluations over period \(T\).

Figure 2. Illustration of the Pragmatic Information Index over all points of temporal dimension for the Beta band; (a) for one trial, (b) for all 39 trials. Figures (a) and (b) show the pragmatic information index based on [15]: Pragmatic Information Index, \(H_\ast(t)\) (top), Analytic Amplitude squared, \(A(t)^2\) (middle), and Euclidean distances, \(D_e\) (bottom). Figure 2 illustrates the typical behavior of the original pragmatic information defined according to Eq. 3, following [15]. Data over the beta band are shown for a single channel (Fig. 2a), and all channels (Fig. 2b). In Fig. 2a the peaks in the mean of the squared analytic amplitude \((\text{MA2}(t))\) correspond to peaks in \(H_\ast(t)\) during the \(3 \sim 4s\) period. Fig. 2b also have several MA2(t) peaks but the direct correspondence with \(H_\ast(t)\) is less obvious due to the variation across the 39 trials.
The choice of the index depends on the identification task to be solved.

Figure 3 depicts the trial spatial averages (dashed lines) together with the overall mean value for the 39 trials (solid line), for the alpha band at 2 windows T. Five types of Pragmatic Information Indexes are shown. From top to bottom: HSAA (Eq. 6), He version 1, He version 2, HRSA (Eq.4), HRAA (Eq. 5), respectively. All these Indexes show similar behavior with some subtle differences during the analyzed period for windows T=0.0625 seconds and T=0.125 seconds. The important difference between He in Eq. 3 and all other indices in Fig. 10 is that He uses ED based on analytic amplitude measures, see Eq.1, while the indices we introduced use a new definition of ED based on the analytic phases in consecutive time steps. We will see that the choice of the index depends on the identification task to be solved.

Figure 4 shows the mean index values calculated over different trials. While averaging across trials clearly ignores subtle differences between trials, nevertheless, it is also useful in finding out some persistent features of the post-stimulus response of the subjects. A general observation is that all indices show significant increase between 3.2 s and 4 s. In other words, these indices filter out the initial strong impact of the sensory stimulus caused by the imprint of the sensory data through the sensory tracts, on the cortex. This imprint has been called Type I response and it does not involve higher cognitive functions [24]. In addition, there seems to be 2 major peaks in the 3.2 to 3.8 s period. The details of these effects are studied using further frequency bands (beta and gamma), as described next.
Having a close look at Fig. 5 (beta band analysis) and Fig. 6 (gamma band), we can see clearly the delay in the onset of the increase in value in all indexes for all windows. Also we can observe that the two predominant peaks in the beta band on Fig. 5 are dramatically different in size in contrast with the peaks observed in the alpha band, which are similar in magnitude. For the Gamma band in Figure 6, we observe the presence of more than two peaks (3 or 4). Significant peaks are found for $T = 0.0625$ s (left column). This window size is considered optimum for the gamma band by Freeman which almost coincide with $T = 0.06$ s minimum window size according to Freeman’s method [11, 12]. When contrasted with window size $T = 0.125$ s, we observe decreased resolution, i.e., the peaks merge into 2 peaks for the majority of indexes and to 3 peaks for one of them, see Fig. 13d.

The size of the peaks tends to behave differently for the indexes calculated according to Freeman’s method (c, e) and the rest of the indexes Figure 13 (a, g, and h) for $T=0.0625$ (left column). Overall the observed effects reveal the synchronization between bands of de-synchronization within bands post stimuli for the period between the 3rd and the 4th second.

IV. DISCUSSIONS

Based on the introduced experimental findings, we can make some important remarks. Clearly, the period between 3-4 s is significantly different from the rest of the time segments for all frequency bands. In that period, the moments between 3-3.5 s and between 3.5-4 s are also significantly different.
We observe that the onset of detectable neural events post stimuli happens a little bit after the 3rd second showing a two-peak process that finishes just around the 4th second. Earlier analysis revealed two types (Type I and Type II) of discriminable AM patterns in the (visual) sensory cortex [23]. Type I occurs with short latency after the stimulus (within 0.2s). Type I AM pattern represents the direct impact of a discriminated stimulus on the activity of the receiving cortex. Type II classifiable AM pattern is delayed and it occurs with variable latency within 1 s of the stimulus. It is endogenous and the result of complex transformations through the divergent-convergent neural pathways. Type II AM pattern has been interpreted as the indication of chaotic self-organization of cortical dynamics as the result of sensory input-induced destabilization. Interestingly, these studies did not find meaningful AM patterns in the period 0.2 s to 0.6 s following the stimulus. This may point to the lack of classifiable AM pattern during the transition period between Type I and Type II effects.

This poses the possibility to formulate a new hypothesis where a more accurate understanding of the cycle of knowledge creation may be achieved. It is likely that each band tells us a story about the cycle of knowledge creation in the cortex, which is necessary for intentional behavior. Different bands give us different clues for what to look when searching for cognitively relevant features. For example, theta band shows the beginning and end of the cognitive/learning cycle, so acting as a gating band. Alpha gives us the different significant nonlinear events within the cycle, namely:

- **Step 1 (3 - 3.1 s):** Initial impression, which may be termed the "Awe" moment.
- **Step 2 (3.1 – 3.3 s):** Chaotic Exploration of memory traces with highly distributed and desynchronized patterns.
- **Step 3 (3.3-3.45 s):** Recognition/identification of the searched clue/decision and it can be termed the "Aha" moment.
- **Step 4 (3.45 – 3.6 s):** Integration of the new knowledge in a chaotic dynamic process.
- **Step 5 (3.6 – 3.9 s):** Dramatic drop in the indices toward the end of the post-stimulus brain activity, showing a return to the usual, background level.

In addition we hypothesize that beta could be showing us that other complexities, perhaps the consumption of energy or the amount of work done in each stage in order to create knowledge differs from stage to stage. This could mean that the first part of the cycle is more energy consuming (big peak) than the 2nd half of the cycle (small peak). The gamma band may pose even more refined level of complexities, which remains difficult to assess at the present time.

We have introduced a methodology for Brain Signal Analysis based on rabbit electrocorticogram (ECoG). This mathematical methodology introduces a set of indexes and ratios to detect the onset of synchronization of neural activity across large cortical areas during high-level cognitive functions and awareness experience. It is also important to mention that our hypothesis coincides with Freemans's views on the construction of knowledge and meaning. In fact many of the ideas we put in practice and explore where inspired by his body of research and life work, as well as the work of A. Katchalsky in brain dynamics and the thermodynamics of flow processes in biological systems, respectively. The novelty of our ideas lies in establishing a research framework through EEG for studying the emergence of creative insight and spiritual experience by finding neurodynamic attributes of meaning and knowledge in brains, together with states reflecting peace, compassion, love and humor.

The creation of meaning and knowledge arises in cortical activity rather than in sensory input. Our indexes of Pragmatic Information are initial steps towards a quantitative characterization of Freeman’s cinematic cognitive cycle, which is extremely valuable to understand the nature of meaning in brain dynamics and the action-perception cycle.

V. CONCLUSIONS AND FUTURE PERSPECTIVES

In this work we analyzed ECoG data and identified synchronization effects with sudden transitions in spatio-temporal neurodynamics in the brain of the rabbit. The observed effects can be interpreted using chaotic brain theory, involving phase transitions. If brains exhibit critical phase transitions, then scale-free behavior is expected to take place during cognitive states near criticality. Such scale-free behavior should include time dimension, spanning across a range of frequencies, and spatial scales as well. The observed post-stimulus events detected by various indices based on pragmatic information, provide supporting evidence to this hypothesis.

The analyzed response period shows various significant nonlinear events within the cognitive cycle in the 1 s window following stimuli. We propose an interpretation of the findings as follows. Starting with “Awe” (3-3.1 s), chaotic exploration (3.1-3.3 s) follows, leading to the “Aha” (3.3-3.45 s) moment. Next, chaotic integration (3.45-3.6 s) takes place and finally a dramatic drop (0.6-0.9 s) indicates a return to the basal brain dynamics. The present analysis provides important details on cognitive processing exactly during the critical transition period, during which the subject solves the classification task.

Future studies are planned by measuring EEG activity in humans while in states of relaxation, peaceful existence, and physiological coherence mediated by breathing, and compare with mental activity while engaged in unpleasant energy depletion activities leading eventually to stress. Various experimental approaches will be useful to find the answer to these challenging questions. We hope our findings based on EEG analysis motivate further studies towards the identification of neural correlates of cognition and awareness experience through the integration of various experimental paradigms.

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